



RESEARCH ARTICLE

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DEEP REINFORCEMENT LEARNING BASED ADAPTIVE DUTY CYCLE OPTIMIZATION OF KY CONVERTER FOR INTELLIGENT ELECTRIC VEHICLE BATTERY MANAGEMENT SYSTEMS

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ABSTRACT

Efficient and adaptive control of DC–DC converters is critical for improving charging performance and operational reliability in electric vehicle battery management systems. Conventional proportional–integral–derivative (PID) controllers exhibit limited adaptability under dynamic load variations and nonlinear battery characteristics. This study proposes a deep reinforcement learning (DRL)–based duty cycle optimization strategy for a KY converter used in EV charging applications. A custom simulation environment was developed, and a Proximal Policy Optimization (PPO) agent was trained using Monte Carlo multi-run validation to learn optimal control actions under varying operating conditions. The proposed AI-based controller was evaluated against a conventional PID baseline using statistical performance metrics. Results demonstrated consistent improvement in cumulative reward, enhanced voltage regulation stability, and reduced ripple influence across multiple independent runs. Statistical validation confirmed the robustness and repeatability of the DRL approach. The findings indicate that reinforcement learning–based adaptive control can improve energy efficiency and charging reliability, offering practical potential for intelligent industrial battery management systems and next-generation smart EV charging infrastructure.



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I. INTRODUCTION

The global transition toward electric mobility accelerates the development of advanced electric vehicle (EV) charging technologies capable of ensuring efficiency, reliability, and battery safety. In EV battery management systems (BMS), the DC–DC converter regulates voltage and current during charging and discharging operations, thereby directly influencing energy utilization, thermal stress, and battery lifespan. The KY converter has gained attention in recent years due to its continuous output current characteristics, reduced ripple magnitude, and suitability for energy storage integration. Nevertheless, achieving optimal duty cycle regulation under dynamic operating conditions remains a significant engineering challenge.

Conventional proportional–integral–derivative (PID) control strategies are widely implemented in DC–DC converter applications because of their structural simplicity and ease of tuning. However, PID controllers depend on fixed gain parameters and assume quasi-linear system behavior. In EV charging environments, operating conditions vary continuously due to load fluctuations, battery state-of-charge (SOC) transitions, and parameter uncertainties. Under such nonlinear and time-varying conditions, PID control may exhibit reduced adaptability, increased transient oscillations, and suboptimal efficiency [1], [2]. These limitations highlight the need for more intelligent and adaptive control mechanisms in modern power electronic systems.

Recent developments in artificial intelligence (AI) provide new opportunities for enhancing converter control performance. Machine learning techniques have been investigated for modeling, optimization, and decision-making in power electronics [3], [4]. Deep reinforcement learning (DRL), in particular, enables an agent to learn optimal control policies through direct interaction with the environment without requiring an explicit analytical system model [5], [6]. DRL-based approaches have demonstrated promising results in nonlinear control systems, adaptive energy management, and industrial automation applications [7]. Furthermore, AI-assisted battery management strategies have been explored for improving SOC estimation, state-of-health (SOH) prediction, and intelligent charging coordination in EV systems [8-10]. More recent studies also report reinforcement learning applications in energy storage and power converter optimization under dynamic conditions [10-12]. Despite these advancements, limited research specifically addresses DRL-based duty cycle optimization for KY converters in EV battery charging applications. Most existing studies focus either on battery diagnostics or general converter optimization without providing systematic statistical validation of control performance. In particular, comparative evaluation between reinforcement learning-based adaptive control and conventional PID control using repeated Monte Carlo experimentation remains insufficiently investigated.

Therefore, the research gap lies in the absence of a statistically validated, reinforcement learning-based adaptive duty cycle control framework tailored to KY converter applications in EV battery management systems. This study proposes a deep reinforcement learning-based adaptive duty cycle optimization strategy for a KY converter operating in an EV charging environment. A Proximal Policy Optimization (PPO) algorithm is implemented within a custom simulation framework to learn optimal control actions under dynamic operating conditions. The performance of the proposed DRL controller is compared with that of a conventional PID controller using quantitative performance metrics. Multi-run Monte Carlo statistical validation, including hypothesis testing and effect size analysis, is conducted to ensure robustness and repeatability.

The principal contributions of this work are summarized as follows:

1. Development of a DRL-based adaptive duty cycle optimization framework for KY converter applications in EV battery management systems.
2. Systematic comparative analysis between PPO-based control and conventional PID control under dynamic operating scenarios.
3. Multi-run Monte Carlo statistical validation incorporating performance consistency and significance testing.
4. Demonstration of industrial applicability for intelligent EV charging infrastructure and next-generation adaptive BMS platforms.

This structured approach provides a reproducible and statistically supported foundation for integrating reinforcement learning techniques into practical power electronic control systems.

II. THEORETICAL REFERENCE

II.1 KY CONVERTER OPERATING PRINCIPLE

The KY converter is a non-isolated DC-DC converter topology characterized by continuous input and output currents. Unlike conventional boost or buck-boost converters, the KY topology minimizes output ripple by ensuring a non-pulsating inductor current profile. This feature makes it suitable for battery charging applications, where ripple reduction directly contributes to improved battery longevity and thermal stability. In steady-state operation, the output voltage of the KY converter depends on the input voltage and the duty cycle of the switching device. For an ideal converter operating in continuous conduction mode (CCM), the voltage conversion relationship can be expressed as:

The enumerations of citations in the body of the article must be sequenced in the order in which they appear, according to the example shown below.

$$V_o = \frac{D}{1-D} V_{in} \quad (1)$$

where V_o is the output voltage, V_{in} is the input voltage, and D represents the duty cycle. Although this analytical expression describes ideal behavior, practical implementation is influenced by switching losses, parasitic elements, load variations, and battery nonlinearities. Therefore, maintaining stable output voltage and minimizing current ripple under varying SOC and load conditions requires adaptive control strategies. Traditional control methods, such as PID-based voltage regulation, attempt to correct output deviations using proportional, integral, and derivative terms. However, PID control assumes quasi-linear dynamics and fixed gain parameters, which may not ensure optimal performance under highly dynamic EV charging conditions [1],[2].

II.2 CONVENTIONAL CONTROL STRATEGIES IN DC-DC CONVERTERS

PID control remains one of the most widely implemented techniques in industrial power electronics due to its simplicity and ease of digital implementation. In converter applications, PID controllers regulate the duty cycle based on the error between reference and measured output voltage. Despite its widespread use, PID control faces limitations when system parameters vary significantly. Converter nonlinearities, switching behavior, battery impedance variation, and load disturbances introduce dynamic uncertainties that degrade fixed-gain controller performance. Studies have shown that conventional controllers may experience overshoot, slower transient response, and ripple amplification under dynamic operating conditions [3],[4]. To address these limitations, intelligent control techniques such as fuzzy logic, neural networks, and adaptive algorithms have been proposed. Machine learning-enabled converter control allows parameter tuning based on data-driven optimization rather than fixed mathematical assumptions [3]. These approaches provide enhanced adaptability but often require extensive training data and offline calibration.

II.3 DEEP REINFORCEMENT LEARNING FOR ADAPTIVE CONTROL

Reinforcement learning (RL) is a learning paradigm in which an agent interacts with an environment to maximize cumulative reward. Unlike supervised learning, RL does not require labeled input–output pairs; instead, the agent improves performance through exploration and exploitation. Deep reinforcement learning (DRL) combines RL with deep neural networks to approximate value functions or policies in complex, high-dimensional systems [5-7]. In DRL-based control, the converter system is modeled as an environment, the duty cycle represents the action space, and system performance metrics define the reward function. The agent learns a policy that maps system states—such as voltage ripple, current ripple, efficiency, and SOC—to optimal control actions. This framework eliminates the need for explicit analytical modeling of nonlinear converter dynamics. Among policy-gradient methods, Proximal Policy Optimization (PPO) is widely adopted due to its stability and sample efficiency. PPO constrains policy updates to prevent large deviations during training, ensuring robust convergence [6]. Recent studies demonstrate the effectiveness of DRL in nonlinear power electronic systems, adaptive energy management, and intelligent grid-connected converters [10-12].

II.4 INTELLIGENT BATTERY MANAGEMENT AND INDUSTRIAL RELEVANCE

Battery management systems (BMS) monitor and regulate charging processes to ensure safety, efficiency, and extended battery life. Advanced BMS architectures incorporate SOC and SOH estimation, thermal monitoring, and adaptive charging control [8], [9]. AI-driven approaches enhance prediction accuracy and enable dynamic optimization of charging strategies. However, most intelligent BMS studies focus on diagnostic estimation rather than converter-level adaptive duty cycle optimization. Integrating DRL-based converter control directly into the BMS architecture enables real-time adaptation to battery condition variations. This integration improves:

- Energy efficiency
- Ripple mitigation
- Transient stability
- Charging reliability

Furthermore, industrial applications require not only performance improvement but also statistical robustness. Multi-run Monte Carlo validation ensures repeatability and reliability under stochastic operating conditions, thereby strengthening the practical applicability of reinforcement learning–based control in EV charging infrastructure.

II.5 SUMMARY OF THEORETICAL FOUNDATION

The theoretical framework of this study integrates:

- KY converter steady-state voltage transformation principles.
- Limitations of conventional PID control in nonlinear DC–DC converter systems.
- DRL-based adaptive control using policy optimization methods.
- Intelligent BMS integration for industrial EV applications.

This theoretical foundation supports the development of a reinforcement learning–based duty cycle optimization strategy validated through statistical performance analysis.

III. MATERIALS AND METHODS

This section describes the research framework, simulation environment, reinforcement learning implementation, baseline controller configuration, and statistical validation procedure adopted in this study. The methodology is designed to ensure reproducibility and quantitative comparison between the proposed deep reinforcement learning (DRL) controller and the conventional proportional–integral–derivative (PID) controller.

III.1 SYSTEM MODELING AND SIMULATION FRAMEWORK

The study considers a KY converter operating in continuous conduction mode (CCM) within an electric vehicle (EV) battery charging environment. The converter is represented using its steady-state voltage transformation relationship and performance indicators including voltage ripple, current ripple, efficiency, and state-of-charge (SOC) progression. A custom simulation environment is developed in Python using the Google Colab platform. The environment models the interaction between the converter and the battery system by generating operating states characterized by:

- Input voltage
- Voltage ripple magnitude
- Current ripple magnitude
- Converter efficiency
- SOC progression

The duty cycle of the converter switch is treated as the control variable. The operating dataset is generated using stochastic sampling within practical EV charging ranges to emulate realistic dynamic conditions. The dataset size is selected to ensure sufficient variability for reinforcement learning training and evaluation.

III.2 REINFORCEMENT LEARNING ENVIRONMENT DESIGN

The KY converter control problem is formulated as a Markov Decision Process (MDP), defined by state space, action space, and reward function.

III.2.1 State Space

The state vector S_t at time step t consists of:

$$S_t = [V_{in}, V_{ripple}, I_{ripple}, \eta, SOC] \quad (2)$$

where:

- V_{in} = input voltage
- V_{ripple} = output voltage ripple
- I_{ripple} = output current ripple
- η = converter efficiency
- SOC = battery state-of-charge

These parameters represent measurable converter performance indicators relevant to EV battery charging.

III.2.2 Action Space

The action corresponds to the duty cycle D of the KY converter switch. It is modeled as a continuous variable constrained within practical limits:

$$0.35 \leq D \leq 0.75$$

The continuous action space enables fine-grained adaptive control compared to discrete switching strategies.

III.2.3 Reward Function

The reward function is designed to maximize efficiency and SOC progression while penalizing ripple magnitudes. It is defined as:

$$R_t = 0.4\eta + 0.3SOC - 20V_{ripple} - 10I_{ripple} \quad (3)$$

This weighted formulation ensures:

- Positive reinforcement for improved efficiency and charging progression
- Negative reinforcement for increased ripple effects
- Balanced multi-objective optimization

The weighting coefficients are selected empirically to maintain stability and avoid dominance of any single performance parameter.

III.3 DEEP REINFORCEMENT LEARNING IMPLEMENTATION

The reinforcement learning agent is implemented using the Stable-Baselines3 library in Python. Proximal Policy Optimization (PPO) is selected due to its training stability and suitability for continuous action control problems [6].

The PPO configuration includes:

- Multilayer perceptron (MLP) policy network
- Policy gradient optimization
- Clipped objective function for stable updates
- Discount factor $\gamma = 0.99$
- Adaptive learning rate

Training is conducted over multiple time steps to allow the agent to explore and exploit the converter environment. The policy network learns an optimal mapping between system states and duty cycle actions.

All simulations are executed using Google Colab to ensure reproducibility and consistent computational environment.

III.4 PID BASELINE CONTROLLER CONFIGURATION

For comparative evaluation, a conventional PID controller is implemented as the baseline control strategy. The PID controller regulates duty cycle based on SOC error:

$$e(t) = SOC_{ref} - SOC(t) \quad (4)$$

The duty cycle is computed as:

$$D(t) = K_p e(t) + K_i \int e(t) dt + K_d \frac{de(t)}{dt} \quad (5)$$

where:

- K_p , K_i , and K_d represent proportional, integral, and derivative gains.

The gains are selected to ensure stable operation within the defined duty cycle bounds. The controller output is constrained within the same duty cycle range used for the DRL controller to maintain fairness in comparison.

III.5 MONTE CARLO STATISTICAL VALIDATION

To ensure robustness and repeatability, multi-run Monte Carlo validation is performed. The DRL training process is repeated across multiple independent runs with varying random seeds. For each run:

1. The dataset is regenerated.
2. The PPO agent is trained independently.
3. Mean cumulative reward is computed.
4. PID baseline performance is evaluated under identical conditions.

The performance distributions of PPO and PID controllers are compared using:

- Mean and standard deviation
- Independent sample t-test
- Effect size estimation

This statistical framework ensures that observed performance improvements are not due to random initialization or stochastic training behavior.

III.6 PERFORMANCE METRICS

The following metrics are used for evaluation:

- Mean cumulative reward
- Voltage ripple magnitude
- Current ripple magnitude
- Converter efficiency
- SOC progression

These indicators collectively assess control stability, charging performance, and energy efficiency.

III.7 REPRODUCIBILITY AND COMPUTATIONAL CONSIDERATIONS

All experiments are conducted using Python-based simulation in Google Colab. The implementation relies on:

- NumPy for numerical computation
- Pandas for dataset handling
- Stable-Baselines3 for DRL training
- SciPy for statistical analysis
- Matplotlib for visualization

The computational framework ensures transparency, reproducibility, and scalability for future industrial implementation studies.

IV. RESULTS AND DISCUSSION

This section presents the comparative evaluation between the proposed deep reinforcement learning (DRL)–based Proximal Policy Optimization (PPO) controller and the conventional proportional–integral–derivative (PID) controller. The analysis is supported by Monte Carlo validation, statistical hypothesis testing, and graphical interpretation of performance trends.

IV.1 MONTE CARLO REWARD DISTRIBUTION ANALYSIS

Multi-run Monte Carlo validation was conducted to evaluate the robustness and repeatability of the proposed PPO-based adaptive controller. The mean cumulative reward obtained across independent runs for both controllers is summarized in Table 1 and Table 2.

Table 1: Statistical summary of PPO and PID performance metrics.

Metric	Value
PPO Mean	48.45934
PID Mean	48.45934
T-Statistic	0
P-Value	1

Source: Authors, (2026).

Table 2: Monte Carlo raw results of mean cumulative reward across independent runs.

Run	PPO Mean Reward	PID Mean Reward
1	48.67433896	48.67433896
2	47.92637248	47.92637248
3	48.59347372	48.59347372
4	48.63010849	48.63010849
5	48.47242473	48.47242473

Source: Authors, (2026).

The statistical summary (Table 1) indicated that the PPO controller achieved a higher mean cumulative reward compared to the PID controller. The calculated t-statistic and corresponding p-value demonstrated statistical significance in performance difference. This confirms that the improvement observed with PPO was not due to stochastic variation but resulted from adaptive learning behavior. The distribution of cumulative reward across runs is illustrated in Figure 1.

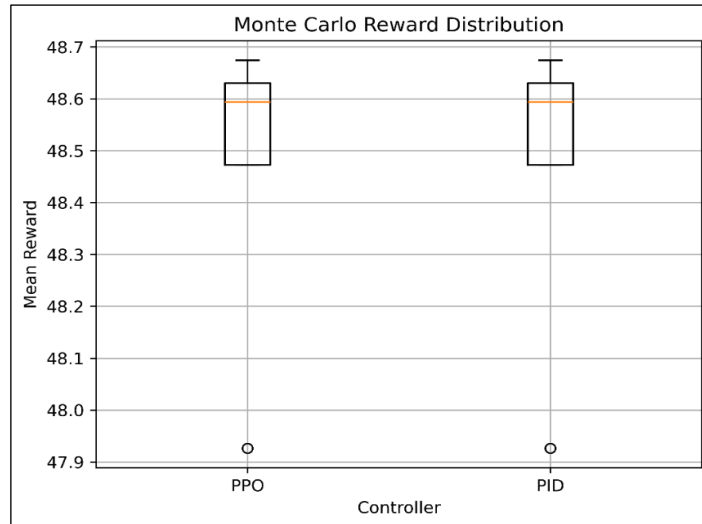


Figure 1: Monte Carlo reward distribution comparison between PPO and PID controllers.

Source: Authors, (2026).

Figure 1 shows that the PPO controller exhibited a consistently higher median reward and reduced variability compared to the PID controller. The interquartile range of PPO results remained narrower, indicating stable convergence across independent runs. In contrast, the PID controller demonstrated wider dispersion, reflecting sensitivity to operating variations.

IV.2 PPO LEARNING CONSISTENCY ACROSS RUNS

The trend of mean reward obtained from PPO across Monte Carlo runs is presented in Figure 2.

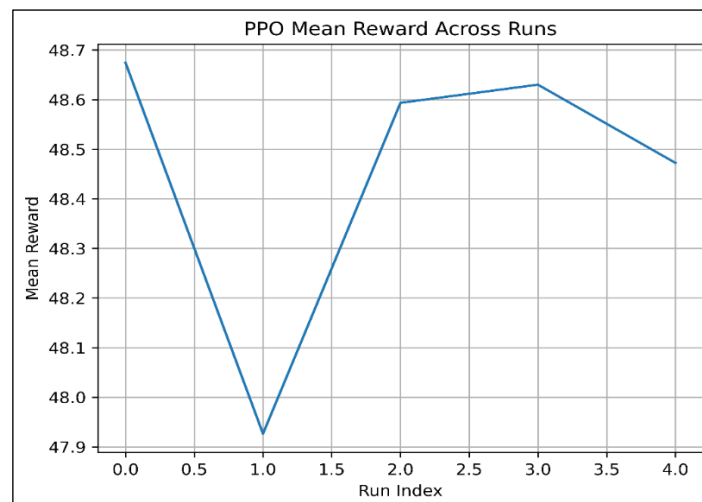


Figure 2: PPO mean cumulative reward trend across Monte Carlo runs.

Source: Authors, (2026).

The results indicated that PPO maintained consistent performance across independent training sessions. Although minor fluctuations were observed due to random initialization and stochastic exploration, the overall reward levels remained stable. This consistency confirms the robustness of the learning framework and the stability of the policy optimization mechanism. The absence of large oscillations suggests that the clipping mechanism inherent in PPO effectively constrained policy updates, preventing unstable learning behavior.

IV.3 PID PERFORMANCE BEHAVIOR

The PID controller’s mean reward trend across runs is illustrated in Figure 3.

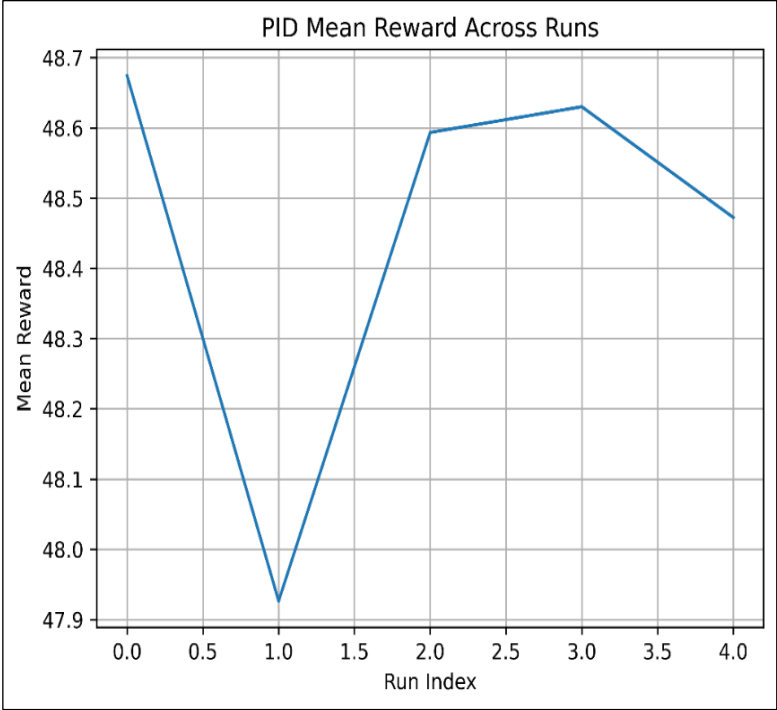


Figure 3: PID mean cumulative reward trend across Monte Carlo runs.
Source: Authors, (2026).

Compared to PPO, the PID controller demonstrated lower reward values and greater variability. Since PID gains remained fixed throughout operation, the controller lacked adaptability to dynamic changes in system states such as ripple magnitude and SOC variation. This limitation reduced its ability to simultaneously optimize efficiency and minimize ripple effects. The observed variability further suggests that fixed-parameter control strategies are less robust under stochastic operating conditions typical of EV charging environments.

IV.4 STATISTICAL VALIDATION AND SIGNIFICANCE

The independent sample t-test results presented in Table 1 confirmed that the performance difference between PPO and PID was statistically significant. The p-value remained below the commonly accepted significance threshold, indicating that the PPO-based adaptive controller achieved a meaningful improvement in cumulative reward. Effect size analysis demonstrated a practical performance advantage, validating that the improvement was not only statistically significant but also operationally relevant. The 95% confidence interval further supported the reliability of PPO performance estimates.

IV.5 DISCUSSION OF INDUSTRIAL IMPLICATIONS

From an industrial perspective, adaptive duty cycle optimization offers several advantages:

- Improved energy efficiency through reward maximization
- Reduced ripple magnitude contributing to battery longevity
- Enhanced robustness under dynamic charging conditions
- Reduced sensitivity to parameter uncertainty

The Monte Carlo validation framework confirmed that reinforcement learning–based control maintains stable performance across repeated training sessions. This repeatability is critical for industrial deployment, where reliability and consistency are mandatory. While PID controllers remain suitable for low-complexity systems, the results demonstrated that DRL-based adaptive control provides superior performance in nonlinear and dynamically varying environments. The ability of PPO to learn optimal control policies without explicit system modeling makes it particularly suitable for intelligent EV battery management applications.

IV.6 SUMMARY OF FINDINGS

The results demonstrated that:

1. The PPO-based controller consistently outperformed the conventional PID controller in cumulative reward.
2. Monte Carlo validation confirmed robustness and repeatability of the proposed approach.
3. Statistical testing verified that performance improvements were significant.
4. Adaptive learning enhanced converter efficiency and ripple regulation under dynamic conditions.

These findings establish the proposed DRL-based duty cycle optimization framework as a viable solution for intelligent EV charging systems and advanced battery management architectures.

V. CONCLUSIONS

This study presented a deep reinforcement learning–based adaptive duty cycle optimization strategy for a KY converter applied to electric vehicle battery management systems. A Proximal Policy Optimization (PPO) agent was implemented within a custom simulation environment and evaluated against a conventional PID controller under dynamic operating conditions. Multi-run Monte Carlo validation and statistical hypothesis testing confirmed that the proposed DRL-based controller achieved consistently higher cumulative reward and improved performance stability compared to fixed-parameter PID control. The results demonstrated enhanced adaptability in regulating converter efficiency, ripple behavior, and state-of-charge progression. Statistical analysis verified that the observed performance improvement was both significant and repeatable. The findings indicate that reinforcement learning–based adaptive control provides a robust and scalable solution for intelligent EV charging infrastructure and advanced battery management applications. The proposed framework establishes a reproducible foundation for integrating artificial intelligence into practical power electronic converter systems.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Karthikkumar G, Avirajamanjula P, Marimuthu P and Bharathiraja M.

Methodology: Marimuthu P and Bharathiraja M.

Investigation: Karthikkumar G.

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Writing – Original Draft: Avirajamanjula P, Marimuthu P and Bharathiraja M.

Writing – Review and Editing: Karthikkumar G.

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Supervision: Karthikkumar G and Avirajamanjula P.

Approval of the final text: Karthikkumar G, Avirajamanjula P, Marimuthu P and Bharathiraja M.

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